For case of y=2, x1, x2 have negative relationship with probability of choosing y=2. If X1, x2 increase by 1 probability of choosing y=2 would decrease by 0.34 and 0.19 times, respectively. But if x3 and X4 increases by 1 probability of choosing y=2 would increase by 2.16 and 6.29 times respectively which is a positive relationship.

Overall Test is significant because prob>chi2 = 0 which is < 0.05.

Pseudo R2 = 29.9% which does not quite fit the data

Individual test x1 and x2 are significant for prob(y=1), the rest are not. For prob(y=2), only Individual test of x2 and x4 are significant, the rest are not.

IIA

```
.  mlogit y x1 x2 x3 x4 if y!=2, base(0) nolog

Multinomial logistic regression                 Number of obs     =         64
                                                LR chi2(4)        =       8.92
                                                Prob > chi2       =     0.0633
Log likelihood = -36.044437                     Pseudo R2         =     0.1101
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
0	(base outcome)					
1						
x1	-.8598281	.5863452	-1.47	0.143	-2.009043	.2893873
x2	-.469266	.7300848	-0.64	0.520	-1.900206	.9616739
x3	-.2417601	.6341053	-0.38	0.703	-1.484584	1.001063
x4	.5911573	.2466463	2.40	0.017	.1077395	1.074575
_cons	-7.329185	3.645689	-2.01	0.044	-14.4746	-.1837657

```
. est store myno2

. hausman my myno2, alleqs constant
```

	---- Coefficients ---- (b) my	(B) myno2	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
x1	-1.038671	-.8598281	-.1788426	.1497051
x2	-.757194	-.469266	-.287928	.1835773
x3	-.4198449	-.2417601	-.1780848	.
x4	.6442446	.5911573	.0530873	.0321568
_cons	-7.719629	-7.329185	-.3904444	.

```
                           b = consistent under Ho and Ha; obtained from mlogit
            B = inconsistent under Ha, efficient under Ho; obtained from mlogit

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        0.72
                Prob>chi2 =      0.9821
                (V_b-V_B is not positive definite)
```

Here, we have prob>chi2 = 0.9821 which is > 0.05. H0 is not rejected. IIA holds in this case. Therefore, **Multinomial Logit is appropriated** here. IIA is where we remove one of the choice but the ratio between choices left is still the same. It's the most important assumption that multinomial logit assumes. If IIA doesn't hold, we can't use this model; we have to use Nested Logit or ASMPProbit instead.

B)

```
. oprobit y x1 x2 x3 x4, nolog

Ordered probit regression                       Number of obs     =        170
                                                LR chi2(4)        =      83.80
                                                Prob > chi2       =     0.0000
Log likelihood = -111.19324                     Pseudo R2         =     0.2737
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	-.2581344	.2285929	-1.13	0.259	-.7061683	.1898996
x2	-.5027724	.2371178	-2.12	0.034	-.9675148	-.0380299
x3	.5101453	.2185012	2.33	0.020	.081891	.9383997
x4	.6963492	.0916125	7.60	0.000	.516792	.8759065
/cut1	9.616274	1.393801			6.884475	12.34807
/cut2	10.87473	1.447773			8.037142	13.71231

X1 and x2 have negative relationship with the dependent variable while x3 and x4 have positive relationship.

X2, x3 , and x4 are significant while x1 is not.

Overall test is significant since prob>chi2 of LR < 0.05.

Pseudo R2 = 27.37% which is quite low

```
. gologit2 y x1 x2 x3 x4, pl sto(oprobit) link(p) nolog

Generalized Ordered Probit Estimates              Number of obs     =        170
                                                  LR chi2(4)        =      83.80
                                                  Prob > chi2       =     0.0000
Log likelihood = -111.19324                       Pseudo R2         =     0.2737

 ( 1)  [0]x1 - [1]x1 = 0
 ( 2)  [0]x2 - [1]x2 = 0
 ( 3)  [0]x3 - [1]x3 = 0
 ( 4)  [0]x4 - [1]x4 = 0

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0            |
          x1 |  -.2581344   .2285929    -1.13   0.259    -.7061683    .1898995
          x2 |  -.5027724   .2371178    -2.12   0.034    -.9675148   -.0380299
          x3 |   .5101453   .2185012     2.33   0.020      .081891    .9383997
          x4 |   .6963492   .0916125     7.60   0.000      .516792    .8759065
       _cons |  -9.616274   1.393801    -6.90   0.000    -12.34807   -6.884475
-------------+----------------------------------------------------------------
1            |
          x1 |  -.2581344   .2285929    -1.13   0.259    -.7061683    .1898995
          x2 |  -.5027724   .2371178    -2.12   0.034    -.9675148   -.0380299
          x3 |   .5101453   .2185012     2.33   0.020      .081891    .9383997
          x4 |   .6963492   .0916125     7.60   0.000      .516792    .8759065
       _cons |  -10.87473   1.447773    -7.51   0.000    -13.71231   -8.037142
------------------------------------------------------------------------------

. gologit2 y x1 x2 x3 x4, npl sto(goprobit) link(p) nolog

Generalized Ordered Probit Estimates              Number of obs     =        170
                                                  LR chi2(8)        =      88.68
                                                  Prob > chi2       =     0.0000
Log likelihood = -108.75253                       Pseudo R2         =     0.2896

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
0            |
          x1 |  -.4923689   .3114572    -1.58   0.114    -1.102814    .1180761
          x2 |  -.4945938   .3491627    -1.42   0.157     -1.17894    .1897526
          x3 |   .1531611   .3254314     0.47   0.638    -.4846727     .790995
          x4 |   .5974751   .1210942     4.93   0.000     .3601349    .8348152
       _cons |  -7.766518   1.863703    -4.17   0.000    -11.41931   -4.113728
-------------+----------------------------------------------------------------
1            |
          x1 |  -.1503435   .2646703    -0.57   0.570    -.6690878    .3684007
          x2 |  -.5375985    .259181    -2.07   0.038    -1.045584    -.029613
          x3 |   .6363866   .2460056     2.59   0.010     .1542245    1.118549
          x4 |   .7345074   .1081653     6.79   0.000     .5225074    .9465075
       _cons |   -11.6244    1.72673    -6.73   0.000    -15.00873   -8.240068
------------------------------------------------------------------------------
```

```
. lrtest oprobit goprobit, stats

Likelihood-ratio test                                 LR chi2(4)  =      4.88
(Assumption: oprobit nested in goprobit)              Prob > chi2 =    0.2997

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
oprobit	170	-153.0946	-111.1932	6	234.3865	253.2013
goprobit	170	-153.0946	-108.7525	10	237.5051	268.863

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

Since P-value of LR > 0.05 Ho is not rejected. Hence, Order Probit model is more appropriated in this case. This means that we have 1 set of beta so coefficients of Ordered Probit is consistent.

C)

```
. probit y1 x1 x2 x3 x4, nolog

Probit regression                               Number of obs     =        550
                                                LR chi2(4)        =      28.90
                                                Prob > chi2       =     0.0000
Log likelihood = -364.50368                     Pseudo R2         =     0.0381
```

y1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	1.405355	.4007082	3.51	0.000	.6199818	2.190729
x2	-.7638351	.3857046	-1.98	0.048	-1.519802	-.0078679
x3	.6079711	.1776757	3.42	0.001	.2597332	.9562091
x4	.2052181	.191227	1.07	0.283	-.16958	.5800161
_cons	-.8378219	.3032075	-2.76	0.006	-1.432098	-.243546

```
. probit y2 x1 x2 x3 x4, nolog

Probit regression                               Number of obs     =        550
                                                LR chi2(4)        =      13.72
                                                Prob > chi2       =     0.0082
Log likelihood = -360.27244                     Pseudo R2         =     0.0187
```

y2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	-.5854516	.3820786	-1.53	0.125	-1.334312	.1634088
x2	-.7301003	.3772512	-1.94	0.053	-1.469499	.0092985
x3	-.229992	.1768496	-1.30	0.193	-.5766109	.1166269
x4	.6221403	.1984953	3.13	0.002	.2330966	1.011184
_cons	.3394003	.3021141	1.12	0.261	-.2527324	.931533

```
. probit y3 x1 x2 x3 x4, nolog

Probit regression                               Number of obs     =        550
                                                LR chi2(4)        =      12.43
                                                Prob > chi2       =     0.0144
Log likelihood =  -329.7597                     Pseudo R2         =     0.0185
```

y3	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	-.6845717	.3924711	-1.74	0.081	-1.453801	.0846575
x2	.8164617	.3892811	2.10	0.036	.0534847	1.579439
x3	-.385427	.1978633	-1.95	0.051	-.773232	.002378
x4	-.2887324	.1895861	-1.52	0.128	-.6603144	.0828496
_cons	-.3847516	.3150829	-1.22	0.222	-1.002303	.2327995

No we shouldn't use 3 separate models because people don't make decisions separately among these 3 choices. There is a relationship when we make decisions among the 3 choices whether to use AIS, DTAC, or TRUE. Choosing 1 choice would affect another choice.

D)

```
. mvprobit (y1 x*) (y2 x*) (y3 x*), nolog

Multivariate probit (SML, # draws = 5)          Number of obs   =        550
                                                Wald chi2(12)   =      40.53
Log likelihood = -932.03719                     Prob > chi2     =     0.0001
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
y1						
x1	1.255116	.3903617	3.22	0.001	.4900207	2.020211
x2	-.6395023	.3795378	-1.68	0.092	-1.383383	.1043782
x3	.5942949	.1786771	3.33	0.001	.2440942	.9444956
x4	.1892288	.1901845	0.99	0.320	-.1835259	.5619834
_cons	-.7708695	.305223	-2.53	0.012	-1.369096	-.1726434
y2						
x1	-.6486226	.3764983	-1.72	0.085	-1.386546	.0893005
x2	-.6305537	.3748293	-1.68	0.093	-1.365206	.1040981
x3	-.2449476	.1784143	-1.37	0.170	-.5946331	.104738
x4	.5843148	.1977095	2.96	0.003	.1968113	.9718184
_cons	.3646932	.3002439	1.21	0.224	-.2237739	.9531604
y3						
x1	-.6049968	.3849896	-1.57	0.116	-1.359563	.149569
x2	.6699129	.3838018	1.75	0.081	-.0823249	1.422151
x3	-.2732464	.1866913	-1.46	0.143	-.6391546	.0926618
x4	-.2533848	.1924329	-1.32	0.188	-.6305464	.1237769
_cons	-.3673441	.3176309	-1.16	0.247	-.9898893	.2552011
/atrho21	-.6107688	.0746482	-8.18	0.000	-.7570767	-.464461
/atrho31	-.4176954	.0740012	-5.64	0.000	-.5627352	-.2726557
/atrho32	-.3267918	.071077	-4.60	0.000	-.4661002	-.1874835
rho21	-.5446681	.0525028	-10.37	0.000	-.6393518	-.433713
rho31	-.3949872	.0624559	-6.32	0.000	-.510004	-.2660942
rho32	-.3156352	.0639959	-4.93	0.000	-.4350429	-.1853173

```
Likelihood ratio test of  rho21 = rho31 = rho32 = 0:
             chi2(3) =  244.997   Prob > chi2 = 0.0000
```

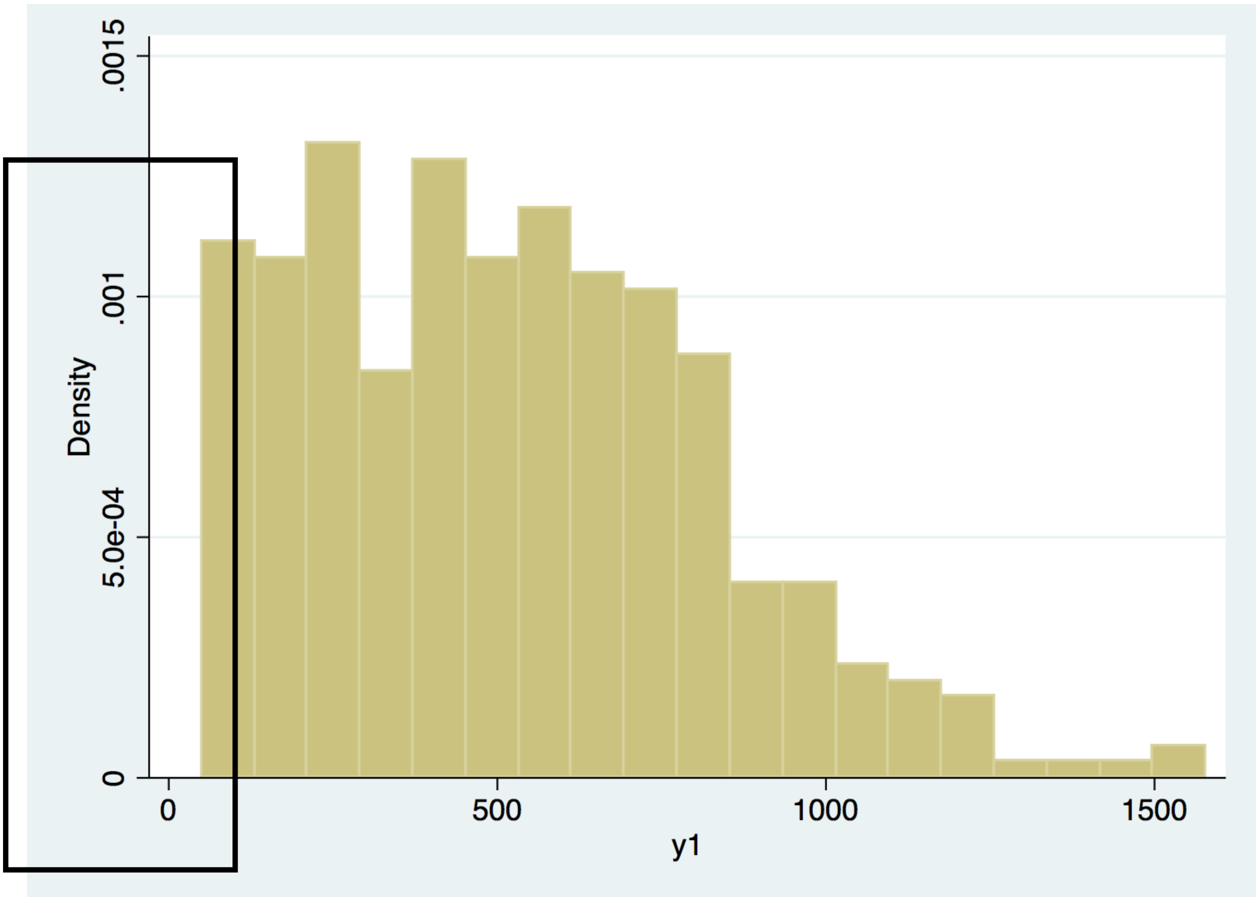
Since p-value < 0.05 so we reject Ho. Ho states that all rho = 0 or there is no relationship among the disturbance terms of these three models. Therefore, there is relationship among them. **MV Probit is more appropriated** since it runs as a system and takes into account the correlation among equations. Even, the specification error might spread but we can't ignore the fact that people don't make decisions on choices separately.

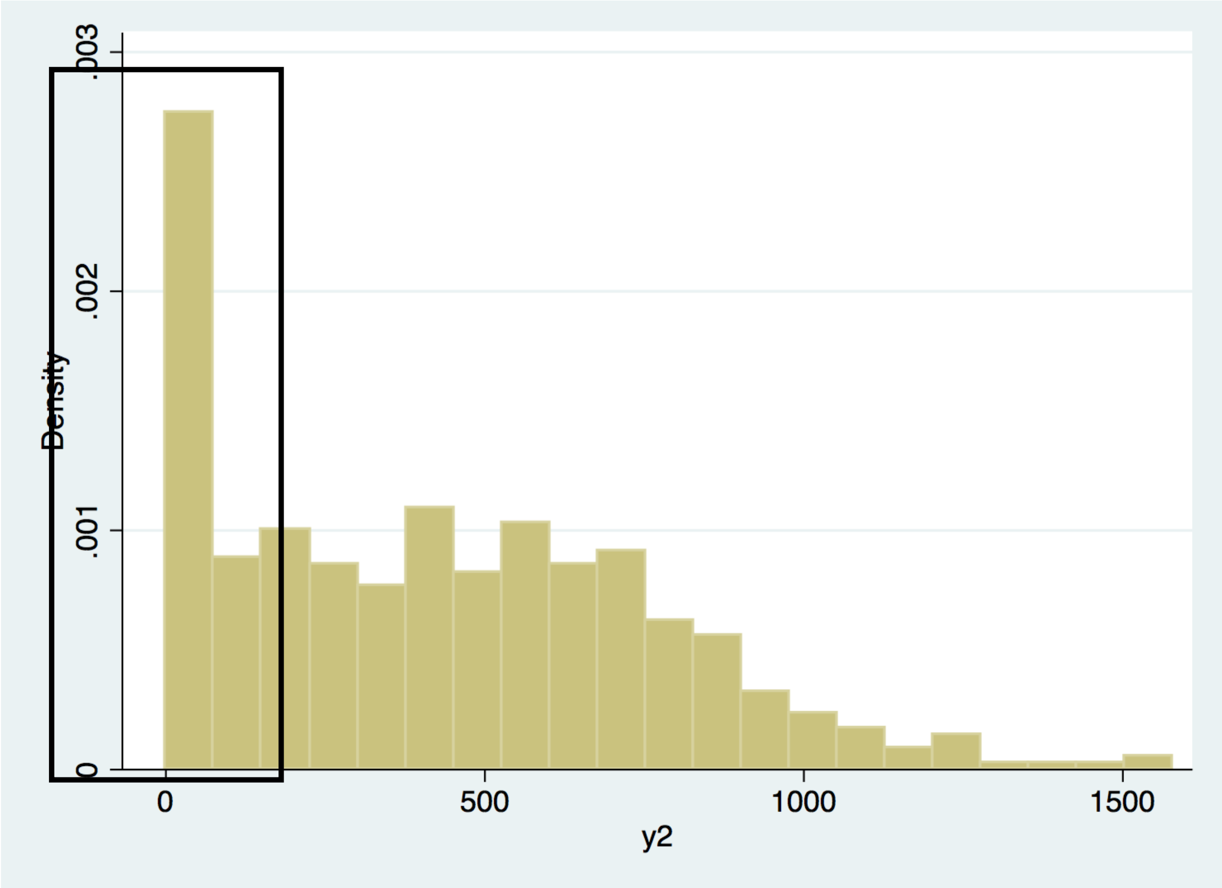
2.

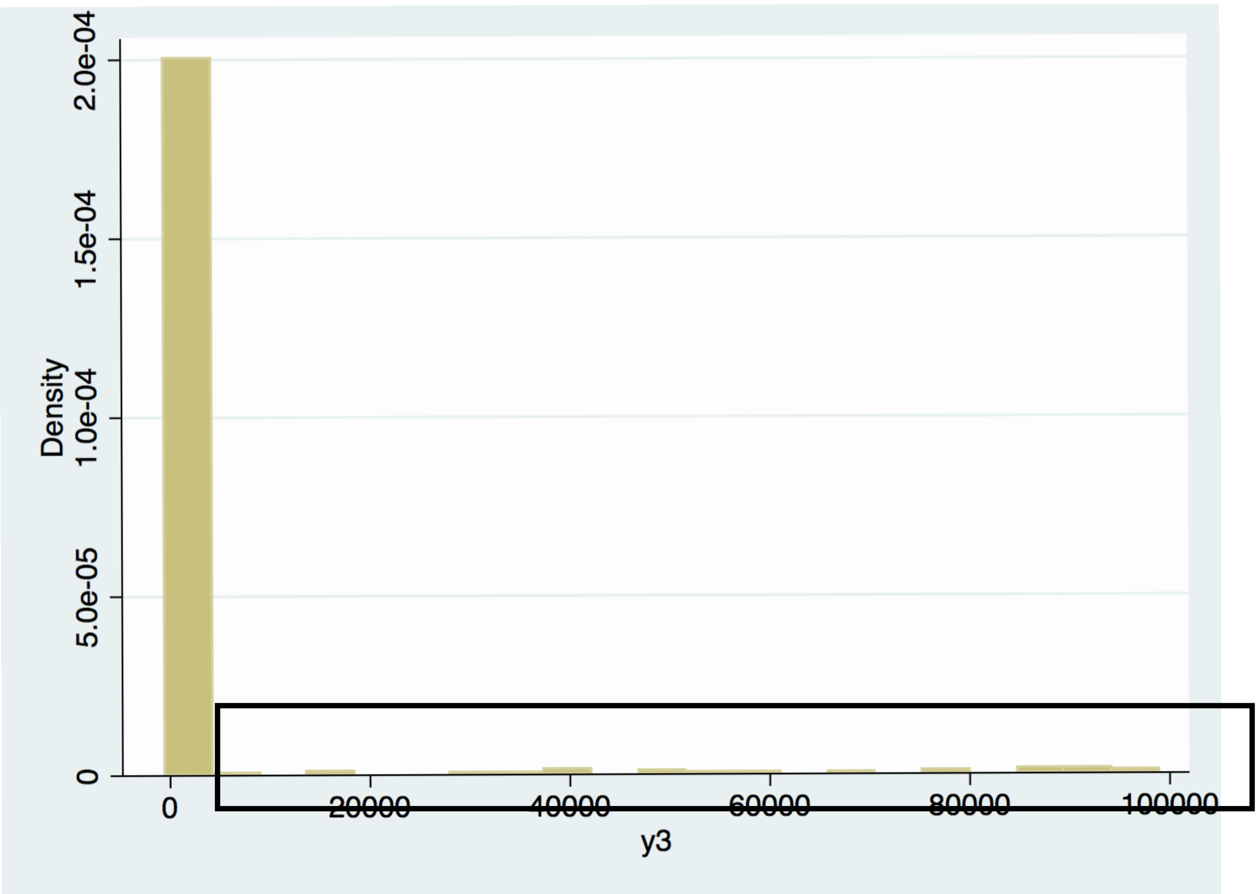
A)

```
. tabstat x y1 y2 y3, stat(N mean med sd min max)
```

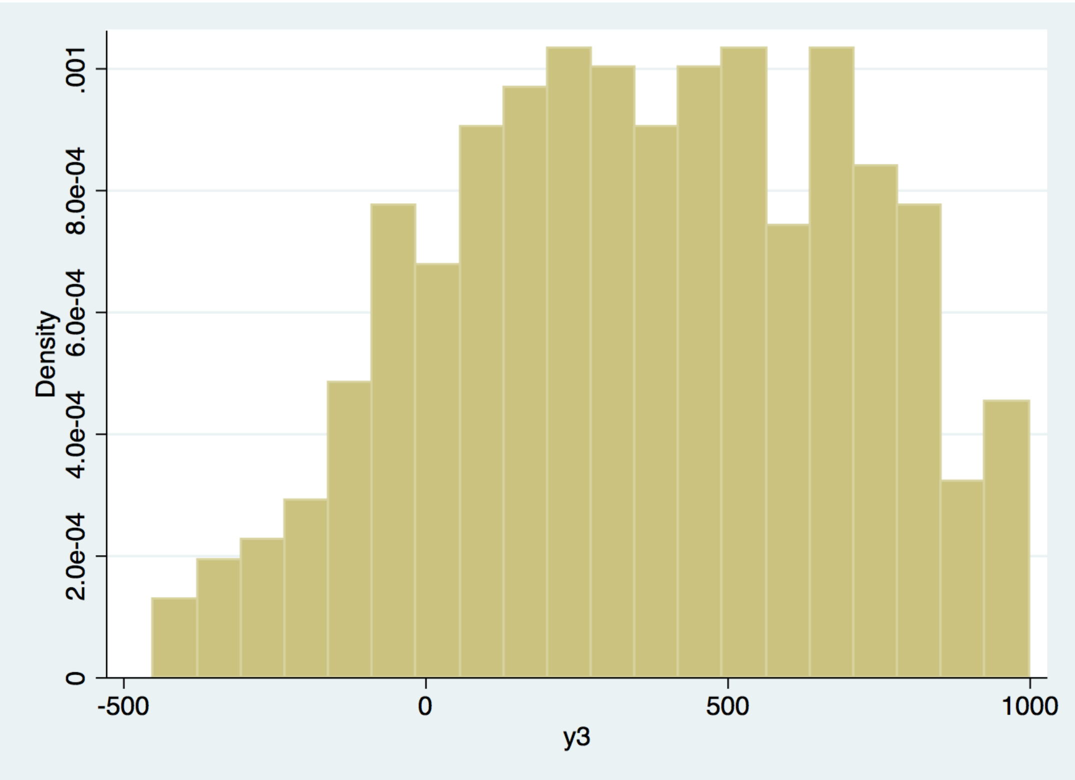
stats	x	y1	y2	y3
N	450	368	450	450
mean	3.010707	520.0403	426.2818	3429.447
p50	2.97671	489.6765	404.0741	404.0741
sd	1.035864	302.8971	338.4643	14734.24
min	.2858976	50.21759	0	-450.6205
max	6.098752	1578.51	1578.51	98951.63




Density
0
.001
.002
.003
0
500
1000
1500
y2


Density
0
5.0e-05
1.0e-04
1.5e-04
2.0e-04
0
20000
40000
60000
80000
100000
y3

```
. sum y3 if y3<2000

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y3 |        427    360.2333      331.77  -450.6205   998.1909

. sum y3 if y3<1000

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y3 |        427    360.2333      331.77  -450.6205   998.1909

. sum y3 if y3<500

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y3 |        269    155.0737    224.5712  -450.6205   497.8316

. sum y3 if y3<1500

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y3 |        427    360.2333      331.77  -450.6205   998.1909

. histogram y3 if y3 < 1000
(bin=20, start=-450.62051, width=72.440572)

. sum y3 if y3 < 900

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y3 |        411    337.0507     316.158  -450.6205   897.6713
```



According to descriptive statistics (mean, med, sd, min, max) and histograms, it might be concluded that y_1 has truncated problem at around 50, y_2 has censored problem at 0, y_3 has outlier problem.

B)

```
. reg y1 x

      Source |       SS           df       MS      Number of obs   =       368
-------------+----------------------------------   F(1, 366)       =    145.15
       Model |  9561413.03         1  9561413.03   Prob > F        =    0.0000
    Residual |  24109609.2       366  65873.2492   R-squared       =    0.2840
-------------+----------------------------------   Adj R-squared   =    0.2820
       Total |  33671022.3       367  91746.6546   Root MSE        =    256.66

------------------------------------------------------------------------------
          y1 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   167.3551   13.89096    12.05   0.000      140.039    194.6712
       _cons |  -17.98072   46.61846    -0.39   0.700    -109.6544    73.69293
------------------------------------------------------------------------------

. est store m_y1


. est store m_y1

. sum y1

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y1 |        368    520.0403    302.8971   50.21759    1578.51


. truncreg y1 x, ll(50) nolog
(note: 0 obs. truncated)

Truncated regression
Limit:   lower =         50                     Number of obs     =        368
         upper =       +inf                     Wald chi2(1)      =     108.00
Log likelihood = -2525.9027                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
          y1 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   237.3236   22.83655    10.39   0.000     192.5648    282.0824
       _cons |  -326.9735   87.64355    -3.73   0.000    -498.7517   -155.1953
-------------+----------------------------------------------------------------
      /sigma |   306.8576   17.04998    18.00   0.000     273.4403     340.275
------------------------------------------------------------------------------

. predict truncated, e(50,.)
```

```
. est store m_y1t

. lrtest m_y1 m_y1t, force

Likelihood-ratio test                                 LR chi2(1)  =     73.67
(Assumption: m_y1 nested in m_y1t)                    Prob > chi2 =    0.0000

.
```

According to significant LR-test between linear regression model and Truncated regression model, H0 is rejected. So it can be concluded that Truncated regression model is a more appropriated model in this case. The major problem here is the truncation where some of the observation of both x and y can't be observed. If we ignore this problem and use OLS, the results would be biased. We will get the mean different from the true one due to the truncated data distribution.

C)

```
. reg y2 x
```

Source	SS	df	MS			
				Number of obs	=	450
				F(1, 448)	=	265.12
Model	19122826.9	1	19122826.9	Prob > F	=	0.0000
Residual	32313741.6	448	72128.8875	R-squared	=	0.3718
				Adj R-squared	=	0.3704
Total	51436568.5	449	114558.059	Root MSE	=	268.57

y2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
x	199.228	12.2357	16.28	0.000	175.1815	223.2745
_cons	-173.5353	38.95296	-4.45	0.000	-250.0885	-96.98206

```
. est store m_y2
```

```
. tobit y2 x, ll(0)

Tobit regression                                Number of obs     =        450
                                                LR chi2(1)        =     217.79
                                                Prob > chi2       =     0.0000
Log likelihood = -2794.4155                     Pseudo R2         =     0.0375

------------------------------------------------------------------------------
          y2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   234.2738    14.5253    16.13   0.000     205.7278    262.8198
       _cons |  -308.6435   47.02247    -6.56   0.000    -401.0549    -216.232
-------------+----------------------------------------------------------------
      /sigma |    300.291   11.10617                      278.4645    322.1175
------------------------------------------------------------------------------
            66  left-censored observations at y2 <= 0
           384     uncensored observations
             0 right-censored observations

. est store m_y2c


. lrtest m_y2 m_y2c, force

Likelihood-ratio test                                 LR chi2(1)  =    720.00
(Assumption: m_y2 nested in m_y2c)                    Prob > chi2 =    0.0000
```

According to significant LR-test between linear regression model and Tobit regression model, H0 is rejected. So it can be concluded that Tobit regression model is a more appropriated model in this case.

The major problem here is the censored data at 0 where value of a lot of y's observations is 0 which it actually doesn't mean 0. Some observations just have no exact value so it reports as 0. If we ignore this problem and use OLS, the results would be biased. We will get the mean different from the true one due to the censored data.

D)

```
. reg y3 x

      Source |       SS           df       MS      Number of obs   =       450
-------------+----------------------------------   F(1, 448)       =     39.59
       Model |  7.9151e+09         1  7.9151e+09   Prob > F        =    0.0000
    Residual |  8.9562e+10       448   199914904   R-squared       =    0.0812
-------------+----------------------------------   Adj R-squared   =    0.0791
       Total |  9.7477e+10       449   217097958   Root MSE        =     14139

------------------------------------------------------------------------------
          y3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   4053.243   644.1646     6.29   0.000     2787.283    5319.202
       _cons |  -8773.681    2050.73    -4.28   0.000    -12803.93   -4743.436
------------------------------------------------------------------------------

. predict y3_hat
(option xb assumed; fitted values)

. est store m_y3


. sum y3

    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
          y3 |        450    3429.447    14734.24  -450.6205   98951.63

. reg y3 x if y3<=1000

      Source |       SS           df       MS      Number of obs   =       427
-------------+----------------------------------   F(1, 425)       =    199.88
       Model |  14999001.5         1  14999001.5   Prob > F        =    0.0000
    Residual |  31891373.7       425  75038.5264   R-squared       =    0.3199
-------------+----------------------------------   Adj R-squared   =    0.3183
       Total |  46890375.2       426  110071.303   Root MSE        =    273.93

------------------------------------------------------------------------------
          y3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   190.4013   13.46731    14.14   0.000     163.9305    216.8721
       _cons |  -197.7743   41.63532    -4.75   0.000    -279.6111   -115.9375
------------------------------------------------------------------------------

. predict y3_hat_o
(option xb assumed; fitted values)
```

```
. est store m_y3o

. tobit y3 x, ul(1000) nolog

Tobit regression                                Number of obs     =        450
                                                LR chi2(1)        =     217.80
                                                Prob > chi2       =     0.0000
Log likelihood = -3050.0734                     Pseudo R2         =     0.0345

------------------------------------------------------------------------------
          y3 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   221.8592   13.46649    16.47   0.000      195.394    248.3244
       _cons |  -266.7015   42.53143    -6.27   0.000    -350.2869   -183.1161
-------------+----------------------------------------------------------------
      /sigma |   289.4279   10.00236                      269.7707    309.0852
------------------------------------------------------------------------------
             0  left-censored observations
           427     uncensored observations
            23 right-censored observations at y3 >= 1000

. est store m_y3o_t


. lrtest m_y3 m_y3o_t, force

Likelihood-ratio test                                 LR chi2(1)  =   3775.92
(Assumption: m_y3 nested in m_y3o_t)                  Prob > chi2 =    0.0000
```

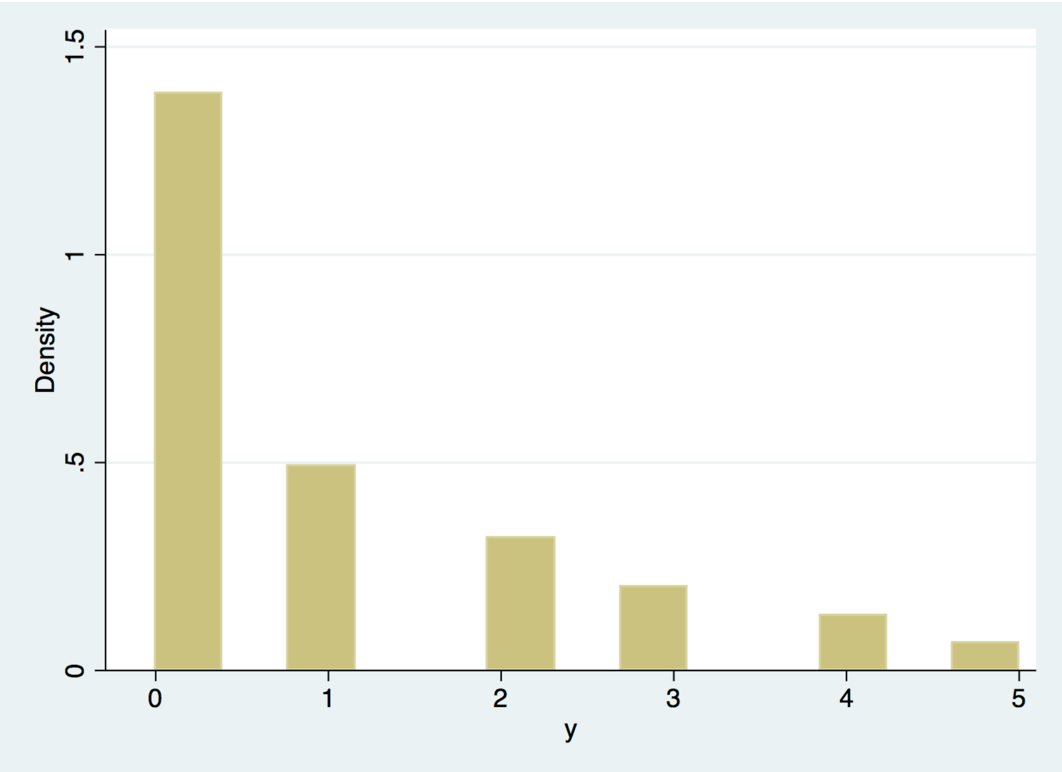
According to significant LR-test between linear regression model and Tobit regression model, H0 is rejected. So it can be concluded that Tobit regression model is a more appropriated model in this case.

The major problem here is the outlier. So we have to clean the data first. The data has outliers above 1000 so we set upper limit = 1000. If we ignore this problem and use OLS, the results would be biased. We will get the mean different from the true one due to the outliers. We might also run OLS with y3<=1000 but we can’t compare this with the other 2 before since number of observations are different.

3.

a)

```
. reg y x1 x2 x3 x4

      Source |       SS           df       MS      Number of obs   =       195
-------------+----------------------------------   F(4, 190)       =      4.90
       Model |  33.4892038         4  8.37230096   Prob > F        =    0.0009
    Residual |  324.510796       190  1.70795156   R-squared       =    0.0935
-------------+----------------------------------   Adj R-squared   =    0.0745
       Total |         358       194  1.84536082   Root MSE        =    1.3069

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   .0807264   .0456416     1.77   0.079    -.0093028    .1707557
          x2 |   .1325927   .0482765     2.75   0.007      .037366    .2278194
          x3 |   .1976082   .0691433     2.86   0.005     .0612211    .3339953
          x4 |    -.03175   .0486008    -0.65   0.514    -.1276164    .0641164
       _cons |   .9424575   .1109718     8.49   0.000     .7235625    1.161352
------------------------------------------------------------------------------

. est store linear

. histogram y
(bin=13, start=0, width=.38461538)
```



There is limitation of dependent variable which is the Poisson distribution. The distribution is discrete. Therefore, the Poisson regression should be used here.

B)

```
. poisson y x1 x2 x3 x4, ir nolog

Poisson regression                              Number of obs     =        195
                                                LR chi2(4)        =      34.13
                                                Prob > chi2       =     0.0000
Log likelihood = -277.16523                     Pseudo R2         =     0.0580

------------------------------------------------------------------------------
           y |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   1.086348   .0380032     2.37   0.018     1.014359    1.163446
          x2 |   1.142059   .0416183     3.65   0.000     1.063333    1.226613
          x3 |   1.232996   .0676214     3.82   0.000     1.107335    1.372917
          x4 |   .9678447   .0358394    -0.88   0.377     .9000893      1.0407
       _cons |   .8657518   .0802725    -1.55   0.120     .7218883    1.038286
------------------------------------------------------------------------------

. est store poisson


. estat gof

         Deviance goodness-of-fit =  322.6633
         Prob > chi2(190)         =    0.0000

         Pearson goodness-of-fit  =   336.213
         Prob > chi2(190)         =    0.0000


. mfx

Marginal effects after poisson
      y  = Predicted number of events (predict)
         =  .91424589
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
      x1 |   .0757192      .03157    2.40   0.016   .013846  .137593  -.313698
      x2 |   .1214417      .03238    3.75   0.000   .057982  .184901   .854067
      x3 |   .1914859      .04829    3.97   0.000   .096835  .286137  -.281319
      x4 |  -.0298809      .03379   -0.88   0.376  -.096102   .03634  -.794147
------------------------------------------------------------------------------
```

According to GOF test, H0 is rejected. Therefore, Poisson might not be appropriated here. We have to test further for the appropriated model.

Sign&Meaning : Looking at IRR, x1, x2, and x3 have positive relationship with prob(y). X1, x2, and x3 increase by 1 unit, y increases by 1.09, 1.14, and 1.23 times respectively. X4 has negative relationship with y where x4 increase by 1 unit, probability of y decreases by 0.97 times.

Looking at marginal effect, x1, x2, and x3 also have positive relationship with y while x4 has a negative one. If x1, x2, x3, and x4 increase by 1 unit, probability of y would change by 0.075, 0.12, 0.19 and -0.03 units respectively.

Overall test is significant since p-value of LR test <0.05

Looking z-test, Only x4 is not significant individually, the rest are.

Pseudo R2 = 5.8% which not quite fit the data

C)

```
. nbreg y x1 x2 x3 x4, ir nolog

Negative binomial regression                    Number of obs     =        195
                                                LR chi2(4)        =      18.21
Dispersion     = mean                           Prob > chi2       =     0.0011
Log likelihood = -261.02656                     Pseudo R2         =     0.0337

------------------------------------------------------------------------------
           y |        IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          x1 |   1.121795     .06142     2.10   0.036     1.007648    1.248872
          x2 |   1.163106   .0616532     2.85   0.004     1.048334    1.290445
          x3 |   1.222813   .0876104     2.81   0.005     1.062611    1.407167
          x4 |   .9648373   .0486177    -0.71   0.477     .8741026     1.06499
       _cons |   .8500949   .1052879    -1.31   0.190     .6668719    1.083658
-------------+----------------------------------------------------------------
    /lnalpha |  -.1277521   .2832588                      -.682929    .4274249
-------------+----------------------------------------------------------------
       alpha |   .8800716    .249288                      .5051353    1.533304
------------------------------------------------------------------------------
LR test of alpha=0: chibar2(01) = 32.28                Prob >= chibar2 = 0.000
```

```
. est store nb

. mfx

Marginal effects after nbreg
      y  = Predicted number of events (predict)
         =  .90703231
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
x1	.1042454	.04949	2.11	0.035	.007247	.201244	-.313698
x2	.1370475	.04792	2.86	0.004	.043128	.230967	.854067
x3	.1824529	.06472	2.82	0.005	.055595	.309311	-.281319
x4	-.032468	.0457	-0.71	0.477	-.12204	.057104	-.794147

According to LR test, H0 is rejected. Therefore, NB is more appropriated than Poisson. Therefore, NB might be appropriated here.

Sign&Meaning : Looking at IRR, x1, x2, and x3 have positive relationship with prob(y). X1, x2, and x3 increase by 1 unit, y increases by 1.12, 1.16, and 1.22 times respectively. X4 has negative relationship with y where x4 increase by 1 unit, probability of y decreases by 0.96 times.

Looking at marginal effect, x1, x2, and x3 also have positive relationship with y while x4 has a negative one. If x1, x2, x3, and x4 increase by 1 unit, probability of y would change by 0.10, 0.14, 0.18 and -0.032 units respectively.

Overall test is significant since p-value of chi2 in LR test <0.05

Looking z-test, Only x4 is not significant individually, the rest are.

Pseudo R2 = 3.37% which not quite fit the data

D)

```
. zip y x1 x2 x3, inflate(x4) vuong nolog

Zero-inflated Poisson regression                Number of obs     =        195
                                                Nonzero obs       =         91
                                                Zero obs          =        104

Inflation model = logit                         LR chi2(3)        =      13.91
Log likelihood  = -259.5176                     Prob > chi2       =     0.0030

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
y            |
          x1 |   .1036952   .0463273     2.24   0.025     .0128954     .194495
          x2 |   .1171252   .0406285     2.88   0.004     .0374948    .1967557
          x3 |   .1482695   .0556119     2.67   0.008     .0392721    .2572668
       _cons |    .358264   .1149163     3.12   0.002     .1330322    .5834957
-------------+----------------------------------------------------------------
inflate      |
          x4 |   .0365686   .0987879     0.37   0.711    -.1570521    .2301892
       _cons |   -.484268   .2520794    -1.92   0.055    -.9783346    .0097987
------------------------------------------------------------------------------
Vuong test of zip vs. standard Poisson:            z =     2.66  Pr>z = 0.0040

. est store zip

. mfx

Marginal effects after zip
      y  = Predicted number of events (predict)
         =  .91849721
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
      x1 |   .0952438      .04227    2.25   0.024   .012402  .178086  -.313698
      x2 |   .1075792      .03662    2.94   0.003   .035797  .179362   .854067
      x3 |   .1361851         .05    2.72   0.006   .038191  .234179  -.281319
      x4 |   -.012576      .03413   -0.37   0.712  -.079462   .05431  -.794147
------------------------------------------------------------------------------
```

According to Voung test, H0 is rejected. Therefore, ZIP is more appropriated than Poisson. Therefore, ZIP might be appropriated here.

Sign&Meaning : Looking at marginal effect, x1, x2, and x3 also have positive relationship with y while x4 has a negative one. If x1, x2, x3, and x4 increase by 1 unit, probability of y would change by 0.095, 0.108, 0.136 and -0.013 units respectively.

Overall test is significant since prob<chi2 of LR test <0.05

Looking at z-test, Only x4 is not significant individually, the rest are.

We don’t have Pseudo R2 here we can look at the log-likelihood value (-259) instead if we want to compare the models.

```
. est table linear poisson nb zip, star(.1 .05 .01) stat(N ll chi2 chi2_c vuong)
```

Variable	linear	poisson	nb	zip
_				
x1	.08072643*			
x2	.13259268***			
x3	.19760816***			
x4	-.03175003			
_cons	.94245746***			
y				
x1		.08282151**	.11493017**	.10369525**
x2		.13283266***	.15109435***	.11712524***
x3		.20944688***	.20115373***	.14826945***
x4		-.03268365	-.03579584	
_cons		-.14415698	-.16240729	.35826398***
lnalpha				
_cons			-.12775205	
inflate				
x4				.03656857
_cons				-.48426798*
Statistics				
N	195	195	195	195
ll	-326.35164	-277.16523	-261.02656	-259.51757
chi2		34.129376	18.205358	13.905119
chi2_c			32.277349	
vuong				2.6553769

legend: * p<.1; ** p<.05; *** p<.01

H0 is GOF test is rejected which suggests that Poisson is not appropriated so we can eliminate Poisson from our choice. Now H0 of LR test of alpha = 0 is rejected which suggests that NB is more appropriated than Poisson. Lastly, H0 of Voung test is rejected which also suggests that ZIP is more appropriated than Poisson. Now we have NB and ZIP to choose. However, when we look at the histogram, we see high density of zero observations. Therefore, ZIP should be the most appropriated one.

4.

A)

```
. tsset t
        time variable:  t, 1 to 500
                delta:  1 unit


. dfuller x, trend lag(1) regress

Augmented Dickey-Fuller test for unit root         Number of obs   =       498

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -15.204            -3.980            -3.420            -3.130
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.x          |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |
         L1. |  -.9860114   .0648513   -15.20   0.000     -1.11343   -.8585931
         LD. |  -.0497438   .0449974    -1.11   0.269    -.1381538    .0386661
      _trend |     .00266   .0030124     0.88   0.378    -.0032587    .0085787
       _cons |   .4111135   .8693903     0.47   0.637    -1.297045    2.119272
------------------------------------------------------------------------------
```

We run the full model with drift, trend, unit root, and lags. We test H0 : Unit Root. Here H0 is rejected. Therefore, there is no unit root problem for x. X is stationary

```
. dfuller y, trend lag(1) regress

Augmented Dickey-Fuller test for unit root         Number of obs   =       498

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -15.051            -3.980            -3.420            -3.130
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.y          |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           y |
         L1. |  -.9744645   .0647443   -15.05   0.000    -1.101673   -.8472564
         LD. |  -.0586809   .0449917    -1.30   0.193    -.1470796    .0297179
      _trend |   .0016658   .0021095     0.79   0.430    -.0024789    .0058105
       _cons |   .8284446   .6113066     1.36   0.176     -.372637    2.029526
------------------------------------------------------------------------------
```

We run the full model with drift, trend, unit root, and lags. We test H0 : Unit Root. Here H0 is rejected. Therefore, there is no unit root problem for y. Y is stationary.

Stationary means we have constant mean, variance, and covariance. If we have Time Series data being Nonstationary, we can't analyze the effect. Stationary would have the mean reversion where the data may deviate from the mean but it will go back to the mean over time. If not so, the error term would keep widening and we wouldn't be able to analyze it. And if we estimate the Nonstationary Time series, we would have false relationship where the coefficient is significant but it's not supposed to theoretically.

B)

For some reason, it says flat log likelihood encountered, cannot find uphill direction arima304. So I will have to compare every models except arima304

```
. qui arima y, arima(3,0,4) nolog
flat log likelihood encountered, cannot find uphill direction
```

```
. est table arima*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

Variable	arima101	arima102	arima103	arima104
y				
_cons	**1.2826409*** **	**1.2843378*** **	**1.2834035*** **	**1.2837639*** **
ARMA				
ar				
L1.	**-.8593362*** **	**.81493824*** **	**-.99829662*** **	**-.82321706*** **
L2.				
L3.				
L4.				
ma				
L1.	**.81738194*** **	**-.85139923*** **	**.96440879*** **	**.79183865*** **
L2.		**.0704514**	**.02168139**	**.02702763**
L3.			**.05315129**	**.05096572**
L4.				**.04872509**
sigma				
_cons	**6.7321752*** **	**6.7328458*** **	**6.7346979*** **	**6.7229014*** **
Statistics				
N	**500**	**500**	**500**	**500**
ll	**-1662.9283**	**-1662.9747**	**-1663.1861**	**-1662.2464**
chi2	**53.804408**	**21.545874**	**9107.2811**	**45.609007**
aic	**3333.8567**	**3335.9493**	**3338.3722**	**3338.4929**
bic	**3350.7151**	**3357.0223**	**3363.6598**	**3367.9951**

legend: * p<.1; ** p<.05; *** p<.01

Variable	arima201	arima202	arima203	arima204
y				
_cons	**1.2843491*****	**1.2850361*****	**1.2845491*****	**1.2849943*****
ARMA				
ar				
L1.	**.72750226*****	**.02216599**	**-.01738108**	**-.03246571**
L2.	**.07499247**	**.72972184*****	**.72686646*****	**.68849885****
L3.				
L4.				
ma				
L1.	**-.76628132*****	**-.04313237**	**-.01700033**	**-.00095294**
L2.		**-.66321636****	**-.66151339****	**-.63672423****
L3.			**.02365016**	**.0230928**
L4.				**.02355742**
sigma				
_cons	**6.7320377*****	**6.7209871*****	**6.7197898*****	**6.7181854*****
Statistics				
N	**500**	**500**	**500**	**500**
ll	**-1662.9177**	**-1662.1195**	**-1662.0086**	**-1661.902**
chi2	**18.586758**	**20.955404**	**22.042526**	**20.869087**
aic	**3335.8355**	**3336.239**	**3338.0173**	**3339.8039**
bic	**3356.9085**	**3361.5266**	**3367.5195**	**3373.5208**

legend: * p<.1; ** p<.05; *** p<.01

Variable	arima301	arima302	arima303	arima401
y				
_cons	**1.2835755*** **	**1.2848818*** **	**1.3008789*** **	**1.2839056*** **
ARMA				
ar				
L1.	**-.85158732*** **	**-.04752986**	**1.0634403*** **	**-.78403607** **
L2.	**.03104064**	**.72806369*** **	**.65816422** **	**.0313108**
L3.	**.02083851**	**.02426849**	**-.83794842*** **	**.05339392**
L4.				**.04990874**
ma				
L1.	**.82128551*** **	**.01403349**	**-1.1201628**	**.75262611** **
L2.		**-.6634085** **	**-.56307227**	
L3.			**.80986878**	
L4.				
sigma				
_cons	**6.7301183*** **	**6.7199519*** **	**6.6381518**	**6.7226835*** **
Statistics				
N	**500**	**500**	**500**	**500**
ll	**-1662.7767**	**-1662.0159**	**-1657.957**	**-1662.2306**
chi2	**55.498393**	**22.656925**	**34384.808**	**38.785237**
aic	**3337.5533**	**3338.0319**	**3329.914**	**3338.4612**
bic	**3362.841**	**3367.5341**	**3359.4163**	**3367.9634**

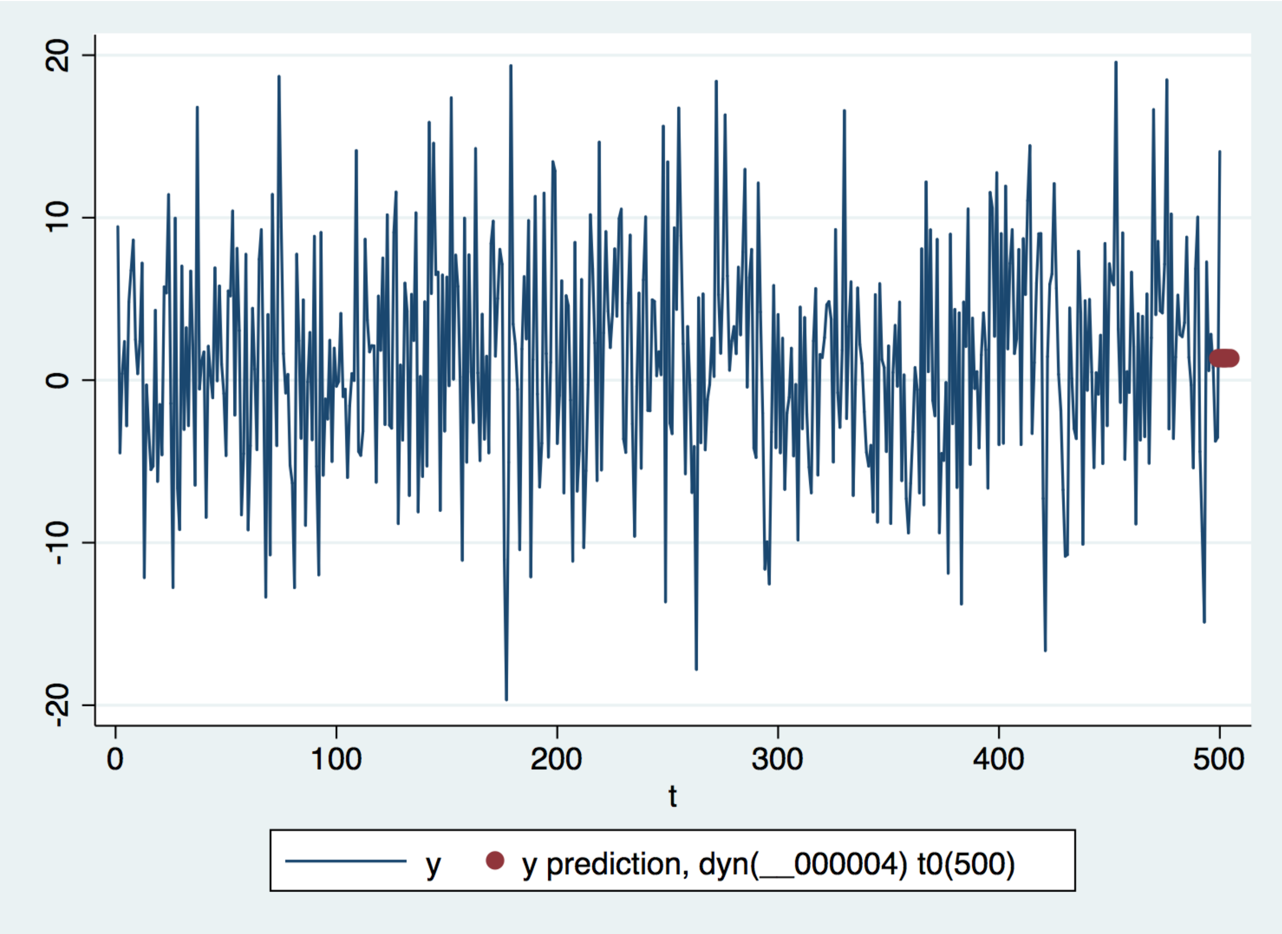
legend: * p<.1; ** p<.05; *** p<.01

Variable	arima402	arima403	arima404
y			
_cons	**1.2847967*****	**1.3008897*****	**1.2856535*****
ARMA			
ar			
L1.	**-.06788343**	**1.0637369*****	**.07186707**
L2.	**.65500012***	**.65774473**	**-.22747828**
L3.	**.02551482**	**-.83795977*****	**-.05636847**
L4.	**.02545987**	**.00016236**	**.70578262*****
ma			
L1.	**.03403946**	**-1.1203481**	**-.10760911**
L2.	**-.60380651**	**-.56271238**	**.31047957**
L3.		**.80968264**	**.05741846**
L4.			**-.6574619****
sigma			
_cons	**6.7181236*****	**6.6381524**	**6.6776732*****
Statistics			
N	**500**	**500**	**500**
ll	**-1661.9025**	**-1657.957**	**-1659.1405**
chi2	**20.298713**	**49315.797**	**1339.1307**
aic	**3339.8051**	**3331.914**	**3338.281**
bic	**3373.522**	**3365.6309**	**3380.4271**

legend: * p<.1; ** p<.05; *** p<.01

According to the value of BIC, Arima(1,0,1) seems to be the most appropriated one.

```
. arima y, arima(1,0,1) nolog

ARIMA regression

Sample:  1 - 500                              Number of obs     =        500
                                              Wald chi2(2)      =      53.80
Log likelihood = -1662.928                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------
             |                 OPG
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
y            |
       _cons |   1.282641   .2963148     4.33   0.000     .7018745    1.863407
-------------+----------------------------------------------------------------
ARMA         |
          ar |
         L1. |  -.8593362   .1624099    -5.29   0.000    -1.177654   -.5410187
             |
          ma |
         L1. |   .8173819    .183682     4.45   0.000     .4573718    1.177392
-------------+----------------------------------------------------------------
      /sigma |   6.732175   .2150834    31.30   0.000      6.31062    7.153731
------------------------------------------------------------------------------
Note: The test of the variance against zero is one sided, and the two-sided
      confidence interval is truncated at zero.

. set obs 505
number of observations (_N) was 500, now 505

. replace time=_n
variable time not found
r(111);

. replace t=_n
(5 real changes made)

. predict yhat, y dynamic(.) t0(500)
Note: beginning dynamic predictions in period         3.
(499 missing values generated)

. twoway (line y t, sort) (scatter yhat t, sort)
```


20
10
0
-10
-20
0
100
200
300
400
500
t
y
y prediction, dyn(__000004) t0(500)

c)

```
. reg y x

      Source |       SS           df       MS      Number of obs   =       500
-------------+----------------------------------   F(1, 498)       =  57348.59
       Model |   22616.747         1   22616.747   Prob > F        =    0.0000
    Residual |   196.39784       498  .394373172   R-squared       =    0.9914
-------------+----------------------------------   Adj R-squared   =    0.9914
       Total |  22813.1448       499  45.7177251   Root MSE        =    .62799

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |   .6976589   .0029133   239.48   0.000      .691935    .7033827
       _cons |   .5175666   .0282663    18.31   0.000     .4620307    .5731025
------------------------------------------------------------------------------

. estat archlm
LM test for autoregressive conditional heteroskedasticity (ARCH)
---------------------------------------------------------------------------
    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |         38.521               1                    0.0000
---------------------------------------------------------------------------
                         H0: no ARCH effects      vs.  H1: ARCH(p) disturbance
```

H0 : alpha1 = alpha2 = … = alphaq = 0 (No ARCH effect)

Ho is rejected. Therefore, there is a significant ARCH-effect

It is classified as LM test because we test based on Restricted model which is OLS.

D)

```
. forvalue p = 1(1)2 {
  2. forvalue q = 1(1)2 {
  3.                display "estimate garch`p'`q'"
  4.                quietly arch y x, garch(1/`p') arch(1/`q') nolog
  5.                estimates store garch`p'`q'
  6. }
  7. }
estimate garch11
estimate garch12
estimate garch21
estimate garch22

.
end of do-file
```

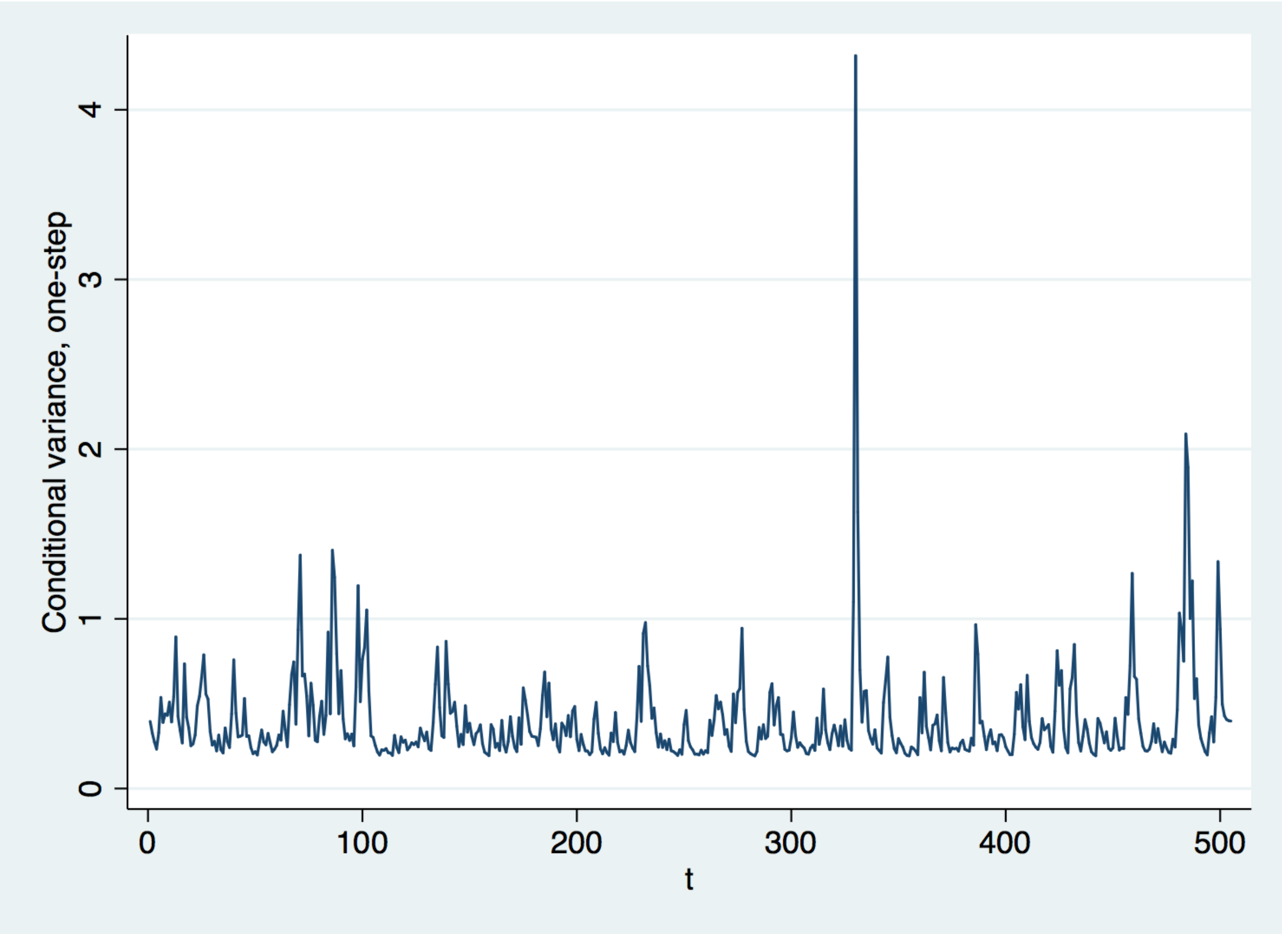
```
. estimates table garch*, star(0.1 0.05 0.01) stat(aic bic ll)
```

Variable	garch11	garch12	garch21	garch22
y				
x	.69777482***	.69776067***	.69776515***	.69765595***
_cons	.51827228***	.51823379***	.51824852***	.51598087***
ARCH				
arch				
L1.	.36232658***	.36071506***	.36109441***	.37211889***
L2.		.01493963		.30804149**
garch				
L1.	.31566651***	.28840547	.3258988*	-.39084269
L2.			-.00926554	.10680766
_cons	.12905173***	.13461573*	.12915411***	.24588848***
Statistics				
aic	898.47349	900.46055	900.46393	900.77814
bic	919.54653	925.74819	925.75157	930.2804
ll	-444.23674	-444.23027	-444.23196	-443.38907

legend: * p<.1; ** p<.05; *** p<.01

```
. qui arch y x, arch(1) garch(1) nolog

. predict sigmahat, v

. line sigmahat t
```

Based on the value of BIC, GARCH(1,1) has the lowest BIC. So the appropriated lags order is GARCH(1,1).


Conditional variance, one-step
0
1
2
3
4
0
100
200
300
400
500
t

E)

```
. arch y x, arch(1) garch(1) egarch(1) nolog

ARCH family regression

Sample: 1 - 500                                 Number of obs   =        500
Distribution: Gaussian                          Wald chi2(1)    =   66852.82
Log likelihood = -447.6815                      Prob > chi2     =     0.0000

------------------------------------------------------------------------------
             |                 OPG
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
y            |
           x |   .6979496   .0026994   258.56   0.000     .6926589    .7032403
       _cons |   .5116242   .0250697    20.41   0.000     .4624885    .5607599
-------------+----------------------------------------------------------------
ARCH         |
      egarch |
         L1. |   .3627247   .1241142     2.92   0.003     .1194654    .6059841
             |
        arch |
         L1. |   .6716952   .0925569     7.26   0.000     .4902871    .8531033
             |
       garch |
         L1. |  -.0061008   .0106959    -0.57   0.568    -.0270644    .0148627
             |
       _cons |  -.9211434   .1570868    -5.86   0.000    -1.229028   -.6132588
------------------------------------------------------------------------------

. est store egarch111

. arch y x, arch(1) nolog

ARCH family regression

Sample: 1 - 500                                 Number of obs   =        500
Distribution: Gaussian                          Wald chi2(1)    =   66170.24
Log likelihood = -449.2486                      Prob > chi2     =     0.0000

------------------------------------------------------------------------------
             |                 OPG
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
y            |
           x |    .697668   .0027122   257.24   0.000     .6923522    .7029837
       _cons |   .5143191   .0246896    20.83   0.000     .4659285    .5627098
-------------+----------------------------------------------------------------
ARCH         |
        arch |
         L1. |   .3817659   .0785455     4.86   0.000     .2278195    .5357123
             |
       _cons |   .2420749   .0222583    10.88   0.000     .1984495    .2857003
------------------------------------------------------------------------------

. est store arch1
```

```
. est table arch1 garch11 egarch111, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

Variable	arch1	garch11	egarch111
y			
x	.69766798***	.69777482***	.69794956***
_cons	.51431911***	.51827228***	.51162418***
ARCH			
arch L1.	.38176588***	.36232658***	.67169519***
garch L1.		.31566651***	-.00610084
egarch L1.			.36272472***
_cons	.24207491***	.12905173***	-.9211434***
Statistics			
N	500	500	500
ll	-449.24864	-444.23674	-447.68153
chi2	66170.236	72657.524	66852.819
aic	906.49729	898.47349	907.36306
bic	923.35572	919.54653	932.65071

legend: * p<.1; ** p<.05; *** p<.01

According to the value of BIC, GARCH(1,1) is the most appropriated here since it has the lowest value.

The 3 models intend to deal with heteroskedaticity in nonlinear model. The difference among these 3 is that ARCH is that variance in ARCH is based on error term only. But for GARCH, it is based on both error term and variance lag terms. EGARCH is when we take exponential of the equations since we prefer to have smooth reaction.

5.

```
. dfuller x, trend lag(1) regress

Augmented Dickey-Fuller test for unit root         Number of obs   =       498

                              ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -15.677            -3.980            -3.420            -3.130
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.x          |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           x |
         L1. |   -.969223   .0618244   -15.68   0.000    -1.090694   -.8477517
         LD. |   .0263952   .0450252     0.59   0.558    -.0620692    .1148597
      _trend |   .0004584   .0003245     1.41   0.158    -.0001791    .0010959
       _cons |   .2054629   .0943259     2.18   0.030     .0201334    .3907924
------------------------------------------------------------------------------


. dfuller y, trend lag(1) regress

Augmented Dickey-Fuller test for unit root         Number of obs   =       498

                              ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)            -14.188            -3.980            -3.420            -3.130
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

------------------------------------------------------------------------------
D.y          |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           y |
         L1. |  -.8505004   .0599455   -14.19   0.000    -.9682799   -.7327208
         LD. |  -.0351351   .0451591    -0.78   0.437    -.1238626    .0535924
      _trend |  -9.29e-06   .0003097    -0.03   0.976    -.0006178    .0005993
       _cons |   .3545866   .0927988     3.82   0.000     .1722576    .5369156
------------------------------------------------------------------------------
```

x and y are Stationary since the test suggests that H0 : Unit root is rejected. Now we can analyze this data further

A)

```
. varsoc x y
```

Selection-order criteria
Sample: **5 - 500** Number of obs = **496**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1366.82				.855276	5.51942	5.52608	5.53638
1	-1319.99	93.661*	4	0.000	.719617*	5.34672*	5.36669*	5.3976*
2	-1319.24	1.4968	4	0.827	.729115	5.35983	5.39312	5.44464
3	-1318.33	1.821	4	0.769	.738257	5.37229	5.41889	5.49102
4	-1316	4.6637	4	0.324	.743243	5.37901	5.43894	5.53167

Endogenous: x y
Exogenous: _cons

According to SBIC, the most appropriated lag order is 1 since it has the lowest SBIC b)

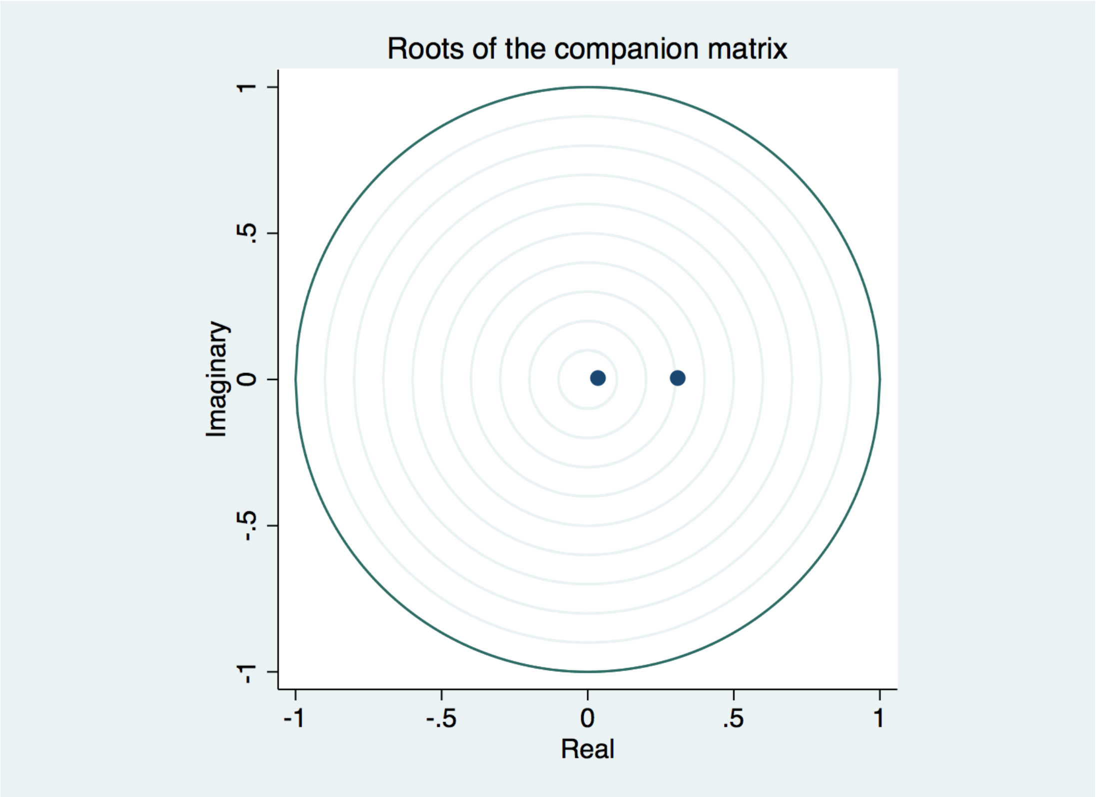
```
. var x y, lag(1/1)

Vector autoregression

Sample:  2 - 500                                Number of obs     =        499
Log likelihood =  -1327.014                     AIC               =   5.342743
FPE            =   .7167624                     HQIC              =   5.362621
Det(Sigma_ml)  =   .6997311                     SBIC              =   5.393396

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
x                     3     .993263   0.0868   47.41994   0.0000
y                     3     .991194   0.0163   8.272547   0.0160
----------------------------------------------------------------

------------------------------------------------------------------------------
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
x            |
           x |
         L1. |   .2073897   .0480723     4.31   0.000     .1131697    .3016098
             |
           y |
         L1. |   .3374705   .0500369     6.74   0.000        .2394     .435541
             |
       _cons |   .1220412   .0543856     2.24   0.025     .0154473    .2286351
-------------+----------------------------------------------------------------
y            |
           x |
         L1. |   .0519038   .0479722     1.08   0.279      -.04212    .1459277
             |
           y |
         L1. |   .1430596   .0499327     2.87   0.004     .0451933    .2409259
             |
       _cons |   .3386196   .0542724     6.24   0.000     .2322477    .4449915
------------------------------------------------------------------------------
```

Here it shows that the overall model is significant.

```
. varstable, graph

   Eigenvalue stability condition
```

Eigenvalue	Modulus
.3114253	.311425
.03902407	.039024

```
   All the eigenvalues lie inside the unit circle.
   VAR satisfies stability condition.
```



From Stability Test, it suggests that Eigen values lie within the unit circle so we have Stability here

```
. vargranger

  Granger causality Wald tests
```

Equation	Excluded	chi2	df	Prob > chi2
x	y	45.487	1	0.000
x	ALL	45.487	1	0.000
y	x	1.1706	1	0.279
y	ALL	1.1706	1	0.279

H0 : No Interdependent

Granger Exogeneity test shows that the effect of y to x is significant. So we can confirm the interdependent as we claimed.

The assumptions of VARs are satisfied here. Because

I) No Unit root — Stationary Time Series data

II) Stability is satisfied

III) Interdependent is ensured by Granger test

If the stability assumption is unsatisfied, we won't be able to analyze further. We can't do Impulse Response Function since it won't go to zero.

```
. irf create order1, o(y x) step(10) set(irf01)
(file irf01.irf created)
(file irf01.irf now active)
(file irf01.irf updated)
```

```
. irf table irf, impulse(x y) response(x y)
```

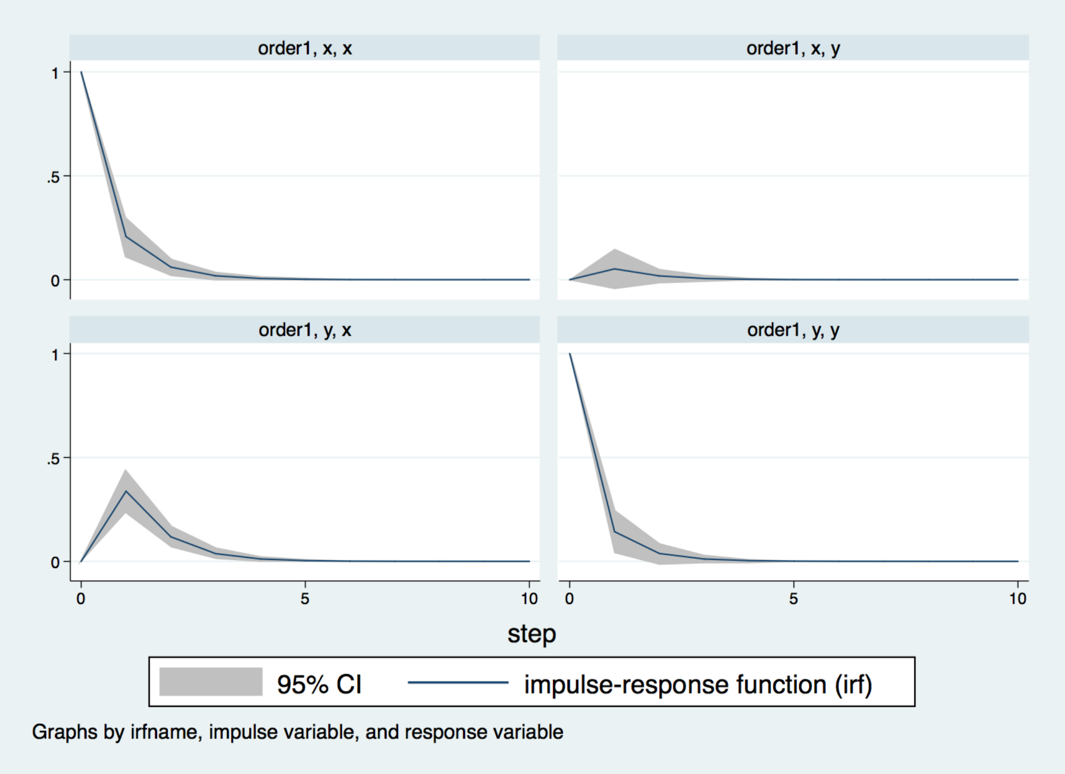
Results from order1

step	(1) irf	(1) Lower	(1) Upper	(2) irf	(2) Lower	(2) Upper
0	1	1	1	0	0	0
1	.20739	.11317	.30161	.051904	-.04212	.145928
2	.060527	.023406	.097648	.01819	-.015115	.051494
3	.018691	.00121	.036173	.005744	-.00641	.017897
4	.005815	-.001665	.013294	.001792	-.002624	.006207
5	.001811	-.001173	.004794	.000558	-.00102	.002136
6	.000564	-.000572	.0017	.000174	-.000382	.000729
7	.000176	-.000243	.000594	.000054	-.000139	.000247
8	.000055	-.000096	.000205	.000017	-.00005	.000083
9	.000017	-.000036	.00007	5.3e-06	-.000017	.000028
10	5.3e-06	-.000013	.000024	1.6e-06	-6.0e-06	9.3e-06

step	(3) irf	(3) Lower	(3) Upper	(4) irf	(4) Lower	(4) Upper
0	0	0	0	1	1	1
1	.33747	.2394	.435541	.14306	.045193	.240926
2	.118266	.06723	.169303	.037982	-.011039	.087004
3	.037345	.012744	.061946	.011572	-.00854	.031684
4	.01165	.000427	.022873	.003594	-.003991	.011179
5	.003629	-.001109	.008367	.001119	-.001649	.003886
6	.00113	-.00075	.00301	.000348	-.000641	.001337
7	.000352	-.000362	.001066	.000109	-.000239	.000456
8	.00011	-.000153	.000372	.000034	-.000087	.000155
9	.000034	-.00006	.000129	.000011	-.000031	.000052
10	.000011	-.000023	.000044	3.3e-06	-.000011	.000017

```
95% lower and upper bounds reported
(1) irfname = order1, impulse = x, and response = x
(2) irfname = order1, impulse = x, and response = y
(3) irfname = order1, impulse = y, and response = x
(4) irfname = order1, impulse = y, and response = y
```

```
. irf graph irf, impulse(x y) response(x y)

. oirf graph oirf, impulse(x y) response(x y)
command oirf is unrecognized
r(199);

. irf graph oirf, impulse(x y) response(x y)

. irf graph coirf, impulse(x y) response(x y)
```



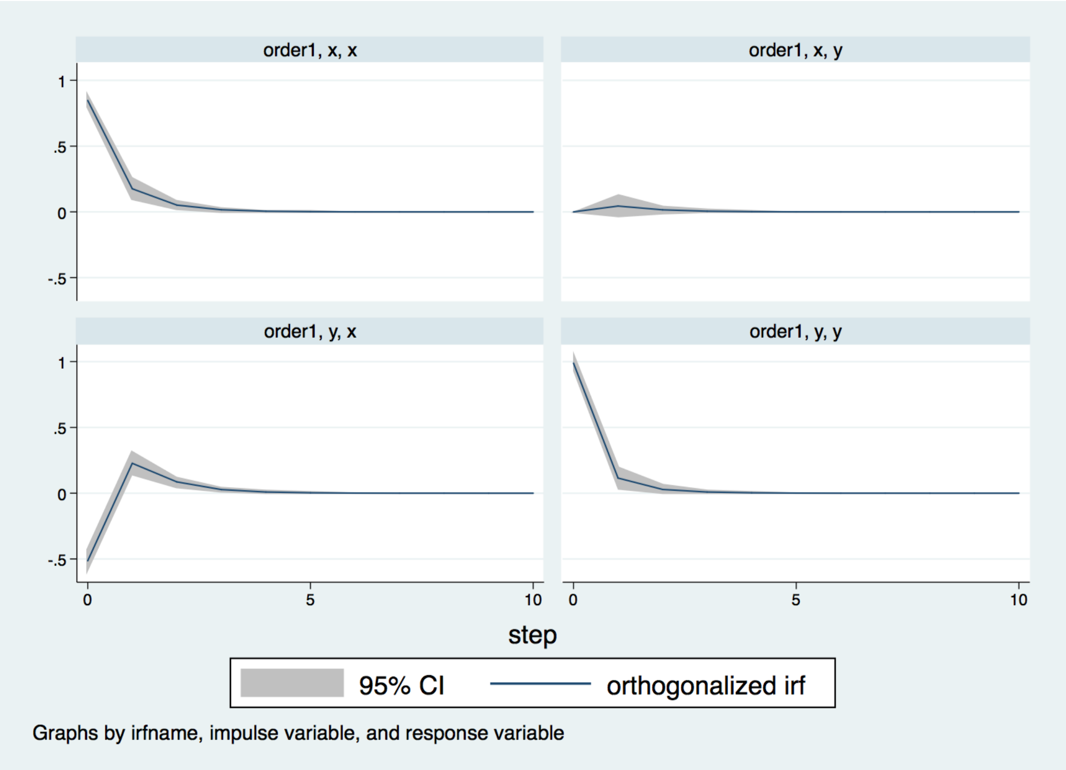

```
. irf table oirf, impulse(x y) response(x y)
```

Results from order1

step	(1) oirf	(1) Lower	(1) Upper	(2) oirf	(2) Lower	(2) Upper
0	.846479	.793962	.898996	0	0	0
1	.175551	.095056	.256047	.043936	-.0357	.123571
2	.051234	.019652	.082817	.015397	-.01281	.043605
3	.015822	.000991	.030652	.004862	-.00543	.015154
4	.004922	-.001417	.011261	.001517	-.002222	.005256
5	.001533	-.000995	.00406	.000472	-.000864	.001809
6	.000477	-.000485	.001439	.000147	-.000323	.000617
7	.000149	-.000206	.000503	.000046	-.000118	.000209
8	.000046	-.000081	.000174	.000014	-.000042	.00007
9	.000014	-.000031	.00006	4.4e-06	-.000015	.000024
10	4.5e-06	-.000011	.00002	1.4e-06	-5.1e-06	7.9e-06

step	(3) oirf	(3) Lower	(3) Upper	(4) oirf	(4) Lower	(4) Upper
0	-.513918	-.594743	-.433093	.98821	.9269	1.04952
1	.22691	.138082	.315738	.114699	.028157	.20124
2	.085766	.046698	.124834	.028186	-.004875	.061248
3	.027299	.009905	.044693	.008484	-.005385	.022353
4	.008525	.000855	.016194	.002631	-.00265	.007911
5	.002656	-.000585	.005896	.000819	-.001119	.002756
6	.000827	-.000468	.002122	.000255	-.000441	.000951
7	.000258	-.000238	.000753	.000079	-.000166	.000325
8	.00008	-.000103	.000264	.000025	-.000061	.00011
9	.000025	-.000041	.000091	7.7e-06	-.000022	.000037
10	7.8e-06	-.000016	.000031	2.4e-06	-7.7e-06	.000012

95% lower and upper bounds reported
(1) irfname = order1, impulse = x, and response = x
(2) irfname = order1, impulse = x, and response = y
(3) irfname = order1, impulse = y, and response = x
(4) irfname = order1, impulse = y, and response = y

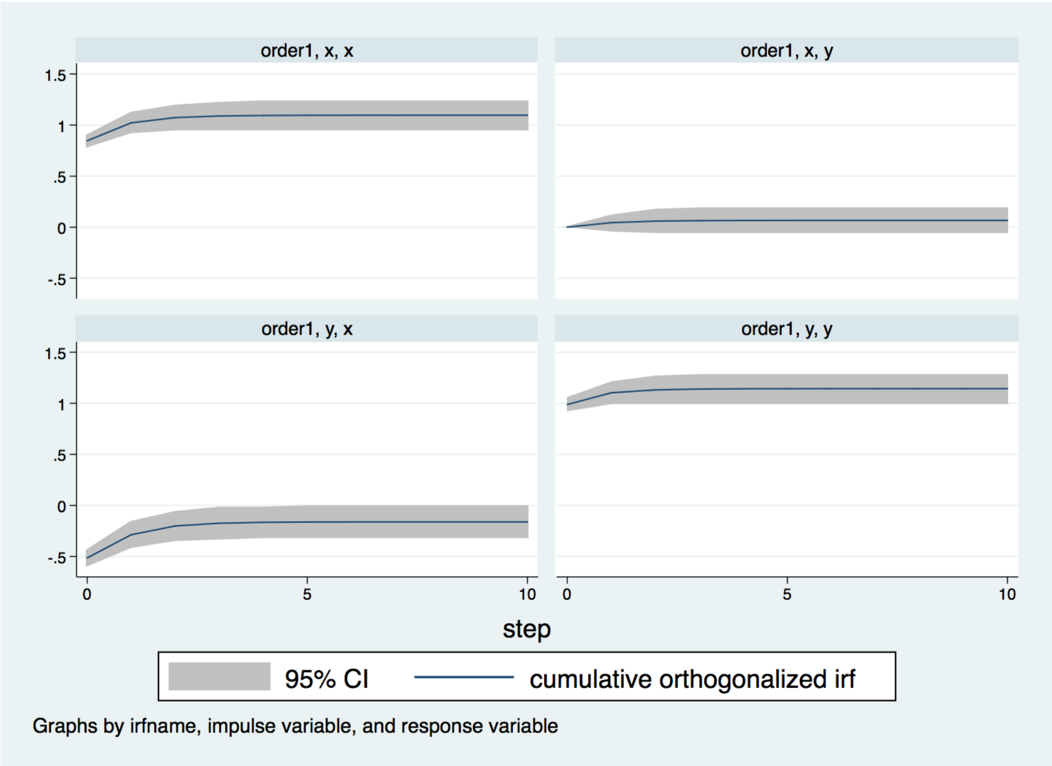



```
. irf table coirf, impulse(x y) response(x y)

                          Results from order1
```

step	(1) coirf	(1) Lower	(1) Upper	(2) coirf	(2) Lower	(2) Upper
0	.846479	.793962	.898996	0	0	0
1	1.02203	.920141	1.12392	.043936	-.0357	.123571
2	1.07326	.950184	1.19635	.059333	-.048151	.166817
3	1.08909	.957375	1.2208	.064195	-.053354	.181743
4	1.09401	.958873	1.22914	.065711	-.055464	.186887
5	1.09554	.959122	1.23196	.066184	-.056278	.188646
6	1.09602	.959137	1.2329	.066331	-.056581	.189243
7	1.09617	.959123	1.23321	.066377	-.05669	.189444
8	1.09621	.959113	1.23331	.066391	-.056729	.189511
9	1.09623	.959108	1.23335	.066396	-.056742	.189534
10	1.09623	.959106	1.23336	.066397	-.056747	.189541

step	(3) coirf	(3) Lower	(3) Upper	(4) coirf	(4) Lower	(4) Upper
0	-.513918	-.594743	-.433093	.98821	.9269	1.04952
1	-.287008	-.412759	-.161257	1.10291	.992813	1.213
2	-.201242	-.342473	-.060011	1.13109	1.00193	1.26026
3	-.173943	-.322327	-.025559	1.13958	1.0025	1.27665
4	-.165418	-.316744	-.014092	1.14221	1.00209	1.28233
5	-.162762	-.315215	-.010309	1.14303	1.0018	1.28425
6	-.161935	-.314799	-.009071	1.14328	1.00167	1.2849
7	-.161678	-.314687	-.008668	1.14336	1.00161	1.28511
8	-.161597	-.314657	-.008538	1.14339	1.00159	1.28518
9	-.161572	-.314649	-.008495	1.1434	1.00158	1.28521
10	-.161565	-.314648	-.008482	1.1434	1.00158	1.28521

```
95% lower and upper bounds reported
(1) irfname = order1, impulse = x, and response = x
(2) irfname = order1, impulse = x, and response = y
(3) irfname = order1, impulse = y, and response = x
(4) irfname = order1, impulse = y, and response = y
```



For the magnitude of impact, looking at coif would be the most convenient. According to coirf, impact of y on x is the highest which is around 0.5 and the direction is negative. While the impact of x on y is only around 0.06 in a positive direction.

d)

```
. irf table fevd, impulse(x y) response(x)
```

Results from order1

step	(1) fevd	(1) Lower	(1) Upper	(2) fevd	(2) Lower	(2) Upper
0	0	0	0	0	0	0
1	.730674	.664132	.797215	.269326	.202785	.335868
2	.703089	.638292	.767886	.296911	.232114	.361708
3	.698995	.634711	.763279	.301005	.236721	.365289
4	.69858	.634357	.762803	.30142	.237197	.365643
5	.69854	.634323	.762757	.30146	.237243	.365677
6	.698536	.634319	.762752	.301464	.237248	.365681
7	.698535	.634319	.762752	.301465	.237248	.365681
8	.698535	.634319	.762752	.301465	.237248	.365681
9	.698535	.634319	.762752	.301465	.237248	.365681
10	.698535	.634319	.762752	.301465	.237248	.365681

95% lower and upper bounds reported
(1) irfname = order1, impulse = x, and response = x
(2) irfname = order1, impulse = y, and response = x

```
. irf table fevd, impulse(x y) response(y)
```

Results from order1

step	(1) fevd	(1) Lower	(1) Upper	(2) fevd	(2) Lower	(2) Upper
0	0	0	0	0	0	0
1	0	0	0	1	1	1
2	.001947	-.005102	.008996	.998053	.991004	1.0051
3	.002183	-.005713	.01008	.997817	.98992	1.00571
4	.002207	-.005786	.0102	.997793	.9898	1.00579
5	.002209	-.005794	.010213	.997791	.989787	1.00579
6	.00221	-.005795	.010214	.99779	.989786	1.0058
7	.00221	-.005795	.010214	.99779	.989786	1.0058
8	.00221	-.005795	.010214	.99779	.989786	1.0058
9	.00221	-.005795	.010214	.99779	.989786	1.0058
10	.00221	-.005795	.010214	.99779	.989786	1.0058

```
95% lower and upper bounds reported
(1) irfname = order1, impulse = x, and response = y
(2) irfname = order1, impulse = y, and response = y
```

In term of variance, impact of y on x (around 0.3) is also higher than x on y (around 0.02)

E)

Yes changing Cholesky order from – "y_t x_t" to "x_t y_t" will change the results of irf, oirf, coirf, and fevd because if order changes, analysis also changes. The order is derived from theory.